MarcXimiL – near-duplicates detection

- flexible, open-source, multi-platform software supporting
- implementation of multiple strategies for record comparisons
- modularity: each task is performed by a function, which may be selected among functions sets that share a common programming interface (in fact Python modules)
- initial double blind test of algorithms (precision, recall)
- lately, focus on speed optimization
- detailed information: http://infoscience.epfl.ch/record/141894
Bibliographic similarity – applications

- merging collections (matching records)
- relevance feedback (more like this / similar records)
- classification (e.g. regroup records for FRBR)
- plagiarism detection (N.B. full-text oriented, but similar)
- collection structure analysis

- near duplicates detection (de-duplication)
Bibliographic records – MARCXML

- **MarcXimiL** has its own internal records representations.
- But uses currently only MARCXML as input.
- **MARCXML** is an XML of the classic MARC format.
- Described in an XML Schema hosted by the U.S. Library of Congress.
- Most library catalogues are in MARC formats (or compatible).
- Possible to **generalize bibliographic similarity analysis by the comparison of MARC records**.
- MARC is sufficient now, but other loading functions may be added easily.
Bibliographic records – MARCXML

- collection (set of bibliographic records)
- record
  - controlfield tag="001"
  - controlfield tag="005"
    - datafield tag="123" ind1="7" ind2="8"
   - datafield tag="456" ind1="9" ind2=""
  - subfield code="a"
  - subfield code="z"

- top level node <collection>
- any number of <record> nodes as children
- fields nodes <controlfield> <datafield>
- subfields nodes <subfield>
Bibliographic records – MARCXML parsing

MarcXimiL MARCXML parsing functions:

- **controlfields**:
  - `parse_controlfield` (usually for system record ids, ex: 001)

- **datafields**:
  - non repeatable fields: `parse_nonrep` (ex: abstract = 520$a)
  - repeatable: `parse_multi` (ex: authors = 100$a + 700$a)
  - concatenation: `parse_concat` (ex: titles+subs = 245$a+245$b)
  - conditional: `parse_conditional` (ex year = 260$c or if absent 269$c)
The LHC experiment aims to improve knowledge of forward neutral particle production spectra at the LHC energy which is relevant for the interpretation of air shower development of high-energy cosmic rays. Two detectors, each composed of a pair of sampling and imaging calorimeters, have been installed at the forward region of the LHC to measure energy spectra above 600 GeV. In this paper, we present a Monte Carlo study of the measurements to be performed with one of the LHC detectors for proton-proton collisions at the LHC energy of 14 TeV. In approximately 40 min of operation at luminosity 10^34 cm^-2 s^-1, the LHC detectors during the beam commissioning phase of LHC, about 1.5 x 10^4 0 events are expected to be obtained at two transverse positions of the detector. The backgrounds from interactions of secondary particles with beam pipes and interactions of beam particles with residual gas in the beam pipes are expected to be less than 0.1% of the signal from #0s. We also discuss the capability of LHC measurements to discriminate between the various hadron interaction models that are used for simulation of high-energy air showers, such as DPMJET3.03, QGSJETII-03, SIBYLL2.1 and EPOS1.99.

article.xml
<collection xmlns="http://www.loc.gov/MARC21/slim">
  <record>
    <controlfield tag="001">1347234</controlfield>
    <controlfield tag="003">SzGeCN/Marcin</controlfield>
    <datafield tag="035" ind="1" subfield code="a">04 Mar 2011</subfield>
    <datafield tag="696" ind="1" subfield code="c">2011</subfield>
    <datafield tag="700" ind="1" subfield code="a">Menjo, H.</subfield>
    <datafield tag="700" ind="1" subfield code="a">Bonechi, L.</subfield>
    <datafield tag="700" ind="1" subfield code="a">Rongi, M.</subfield>
    <datafield tag="700" ind="1" subfield code="a">Castellini, G.</subfield>
    <datafield tag="856" ind="1" subfield code="a">10.1016/j.astrophys.2010.11.002</subfield>
  </record>
</collection>
Monte Carlo study of forward $\pi^0$ production spectra to be measured by the LHCb experiment for the purpose of benchmarking hadron interaction models at 185 GeV.

"At the LHC energy..."
Different strategies for different applications

• Duplicate detection: search for nearly exact matches (high precision), including many different fields – absolute detection threshold important.
• FRBRization: exact matches only, but on a very limited selection of fields?
• Relevance feedback/”More like this”: fuzzier search acceptable, relative ranking matters more
General description of field comparison functions

- Compare fields or sets of fields in two records
- Return a score between 0.0 and 1.0 (or None)
- Divided into several families depending on how we process the field content
RAW field comparison functions

- Similarity score calculated based on the fields in two records
- The rest of the collection doesn't play any role
years_comp__raw()

- Simple decreasing function of the difference in publication year
  $1 - 0.1|\text{year1}-\text{year2}|$

1) `<datafield tag="260" ind1=" " ind2=" ">
   <subfield code="c">2011</subfield></datafield>`

2) `<datafield tag="260" ind1=" " ind2=" ">
   <subfield code="c">2010</subfield></datafield>`

Score = $1.0 - (2011-2010) \times 0.1 = 0.9$
items_comp__raw()

• Fields are treated as sets of values

\[ N(\text{set1} \&\& \text{set2})/N(\text{set1} \mid\mid \text{set2}) \]

• Items in set1 and set2 compared using strict text equality

1) <datafield tag="700" ind1=" " ind2=" "> <subfield code="a">Menjo, Hitomi</subfield> </datafield>
   <datafield tag="700" ind1=" " ind2=" "> <subfield code="a">Adriano, Ottavio</subfield> </datafield>
   <datafield tag="700" ind1=" " ind2=" "> <subfield code="a">Bonechi, Luigi</subfield> </datafield>
   <datafield tag="700" ind1=" " ind2=" "> <subfield code="a">Bongi, Marco</subfield> </datafield>

2) <datafield tag="100" ind1=" " ind2=" "> <subfield code="a">Menjo, H</subfield> </datafield>
   <datafield tag="700" ind1=" " ind2=" "> <subfield code="a">Adriani, O</subfield> </datafield>
   <datafield tag="700" ind1=" " ind2=" "> <subfield code="a">Bonechi, L</subfield> </datafield>
   <datafield tag="700" ind1=" " ind2=" "> <subfield code="a">Bongi, M</subfield> </datafield>
   <datafield tag="700" ind1=" " ind2=" "> <subfield code="a">Castellini, G</subfield> </datafield>

No exact match, the score is zero!
authors_comp__raw()

\[ \frac{N(\text{authors1} \&\& \text{authors2})}{N(\text{authors1} \mid\| \text{authors2})} \]

- Individual names parsed as “Lastname, F” or “Firstname Lastname”

1) <datafield tag="700" ind1=" " ind2=" ">Menjo, Hitomi</datafield>
   <datafield tag="700" ind1=" " ind2=" ">Adriano, Ottavio</datafield>
   <datafield tag="700" ind1=" " ind2=" ">Bonechi, Luigi</datafield>
   <datafield tag="700" ind1=" " ind2=" ">Bongi, Marco</datafield>

2) <datafield tag="100" ind1=" " ind2=" ">Menjo, H</datafield>
   <datafield tag="700" ind1=" " ind2=" ">Adriani, O</datafield>
   <datafield tag="700" ind1=" " ind2=" ">Bonechi, L</datafield>
   <datafield tag="700" ind1=" " ind2=" ">Bongi, M</datafield>
   <datafield tag="700" ind1=" " ind2=" ">Castellini, G</datafield>

\[ \text{Score} = \frac{3}{3 + 3} = 0.5 \]
levenshtein_comp__raw()

- Levenshtein distance $L = \text{minimal number of character modifications to transform string1 into string2}$

$$0 < \exp(-L/L_{\text{par}}) \leq 1$$

- $L_{\text{par}} = 10.0$ by default

1) `<datafield` tag=`"245"` ind1=`" "` ind2=`" "`><subfield code=`"a"`>Monte Carlo study of forward $\pi^0$ production spectra to be measured by the LHCf experiment for the purpose of benchmarking hadron interaction models at $10^{17}$ eV</subfield></datafield>`

2) `<datafield` tag=`"245"` ind1=`" "` ind2=`" "`><subfield code=`"a"`>Monte Carlo study of forward $\pi^0$ production spectra to be measured by the LHCf experiment for the purpose of benchmarking hadron interaction models at $10^{17}$ eV</subfield></datafield>`

$L = 10$, Score = $\exp(-10/10) = 0.3679$
identifiers_comp__raw(),
multiidentifiers_comp__raw()

• Compares two identifiers (or sets of identifiers) and looks for at least 1 shared value.
• Since some identifier conventions are case-insensitive, we convert everything to lowercase.
• Exclude a prefix of 5 chars or less, followed by a colon: it could be just an indication of the identifier type (such as DOI:, ArXiv:, etc), it's easier to neglect it.
isbn_comp__raw()

- Compare sets of ISBNs (10 or 13 digits) looking for at least one shared item
- Return either 1.0 (match found) or 0.0
identifier_synonyms_comp__raw()

- Returns pre-defined scores based on identifiers that we assume to be synonymous or nearly so. Example: ambiguous document types

```python
globalvars.doctype={'08doctype': {'ARTICLE': {'CONF': 0.9}, 'ARTICLE': {'REVIEW': 1.0}}
```
WC field comparison functions

- Similarity score calculated based on indexed fields
- Require indexing the whole collection

We invest some preprocessing time to (hopefully) save more during the comparisons proper.
ntfidf_vectorcosine_wc() et al.

• Vector model of information retrieval: represents documents as vectors over a space of terms (words).
• Component in the dimension of term \( t \): term frequency \( tf \) (# of occurrences of term \( t \)) * inverse document frequency \( idf \) (1 over # of documents containing \( t \)); ntf implies further normalization
• Similarity expressed as a dot product of two vectors (cosine) or other combinations (Dice, Jaccard)
ntfidf_vectordice_wc()
okapibm25__wc()

Normalized Okapi BM25 probabilistic ranking function

• Good ranking function but not suitable for duplicate detection: not equal to 1.0 for identical documents
INITIALS family: items_comp__initials()

- Like RAW, but only the initials of each word are used.

Could be extended to a generalized HASH family in future versions

1) <datafield tag="700" ind1="" ind2="">Menjo, Hitomi</datafield>
   <datafield tag="700" ind1="" ind2="">Adriano, Ottavio</datafield>
   <datafield tag="700" ind1="" ind2="">Bonechi, Luigi</datafield>
   <datafield tag="700" ind1="" ind2="">Bongi, Marco</datafield>

2) <datafield tag="100" ind1="" ind2="">Menjo, H</datafield>
   <datafield tag="700" ind1="" ind2="">Adriani, O</datafield>
   <datafield tag="700" ind1="" ind2="">Bonechi, L</datafield>
   <datafield tag="700" ind1="" ind2="">Bongi, M</datafield>
   <datafield tag="700" ind1="" ind2="">Castellini, G</datafield>

Score = 3/(3+1) = 0.75
SHINGLES field comparison functions

• Like WC, but considering groups of $N$ (4 by default) adjacent words instead of isolated words

• Should be more precise than WC since the word order is taken into account – are you ready to try?

1) {'lhcf experiment for the': 1, 'study of forward $\pi^0$ spectra to be measured': 1, '$\pi^0$ production spectra to': 1, 'measured by the lhcf': 1, 'for the purpose of': 1, 'forward $\pi^0$ production spectra': 1, 'the purpose of benchmarking': 1, 'hadron interaction models at': 1, 'production spectra to be': 1, 'the lhcf experiment for': 1, 'of forward $\pi^0$ production': 1, 'purpose of benchmarking hadron': 1, 'be measured by the': 1, 'models at 10$^{17}$ ev': 1, 'benchmarking hadron interaction models': 1, 'interaction models at 10$^{17}$': 1, 'by the lhcf experiment': 1, 'of benchmarking hadron interaction': 1, 'carlo study of forward': 1, 'to be measured by': 1, 'monte carlo study of': 1, 'experiment for the purpose': 1}
Further families...

- `ntfnidf_vectordice_comp__soundex()`: same as `ntfnidf_vectordice_comp__wc()` but words are reduced to an approximate spelling (or a code number for one) using the Soundex algorithm => more words considered the same.

1) {'e216': 1, 'f600': 1, 'l210': 1, 'b525': 1, 's330': 1, 'f663': 1, 'm530': 1, 'o100': 2, 'a300': 1, '$100': 1, 'e100': 1, 'm263': 1, 'm342': 1, 'c640': 1, 'b000': 2, 't000': 3, 's123': 1, 'h365': 1, 'p632': 1, 'i536': 1, 'p612': 1, '1000': 1}

Score = 0.7672 => higher than than for `ntfnidf_vectordice_comp__wc()`
Similarity strategies – Example

record_rules = geometric_mean
records_comp = records_comp_2collections_luhn
globalvars.luhn_comparisons_field = 'title'
globalvars.output_threshold = 0.75 # use -1 to output everything
record_structure = { "
    'recids' : { 'marc' : '001',
                 'weight' : 0,
                 'parse-func': parse_controlfield,
                 'comp-func' : fields_concat__raw },
    'year' : { 'marc' : '260  c',
                'weight' : 1,
                'parse-func': parse_nonrep,
                'comp-func' : years_comp__raw },
    'title' : { 'marc' : ['245  a', '245  b'],
                 'weight' : 2,
                 'parse-func': parse_concat,
                 'comp-func' : ntfnidf_vectordice_comp__wc },
    'authors' : { 'marc' : ['100  a', '700  a', '9001 a'],
                   'weight' : 1,
                   'parse-func': parse_multi,
                   'comp-func' : authors_comp__raw },
    'source' : { 'marc' : ['773  t', '7112 a'],
                  'weight' : 1,
                  'parse-func': parse_concat,
                  'comp-func' : items_comp__initials } }

Similarity strategies – Python scripts

• Strategies:
  – allow to customize all key aspects of the analysis through a combination of functions (and parameters).

• Modularity:
  – each task is performed by a function, chosen among functions sets that share a common programming interface (Python modules)

• Python:
  – Python has a clean syntax to import modules
  – MarcXimiL is written in pure Python
    (multi-platform, popular, free, clean code, standard library is sufficient)
  – function names are used directly in strategies, new functions may be used at once.
Similarity strategies – Options

1) The way records are compared together \([\text{records\_comp}]\):
   - 1 or 2 collections, Luhn, multi-processing ...

2) The description of the fields to be analysed and functions to compare them \([\text{record\_structure}]\): years/dates, authors, text (title, abstract), identifiers...

3) The combination of fields similarities into record similarities \([\text{record\_rules}]\): weighted means (arithm., geom., harmon.), and ad-hoc functions.

Others: \textit{output\_threshold, luhn\_comparisons\_filed}...
Similarity strategies – record_comp

• Important level for analysis' speed optimization.

• For now, the best option are:
  – `records_comp_single_luhn` or `records_comp_2collections_luhn` on title fields.
  – Variations using authors names are available.
  – We are working on faster ways of doing.

• For a thorough analysis, use:
  – `records_comp_2collections_multiproc` or `records_comp_single_multiproc`
Similarity strategies – Luhn strategy
Similarity strategies – record rules

- Globally, the most efficient is the \texttt{geometric\_mean} function (weighted).
- Some ad-hoc functions also yield good results, like \texttt{ubiquist2} (simplified):
  - Global similarity is set to zero.
  - If identifiers are the same, similarity becomes 1.0
    - and we jump to next record pair
  - Otherwise if author similarity is $\geq 0.85$ and year similarity is $\geq 0.9$
    - records similarity becomes $0.85 \times$ author's similarity.
  - Then abstract and title similarity are computed.
    - records similarity becomes the max of: current record similarity, title similarity, and abstract similarity.
Similarity strategies – deduplication example

```python
record_rules = geometric_mean
records_comp = records_comp_2collections_luhn
globalvars.luhn_comparisons_field = 'title'
globalvars.output_threshold = 0.75 # use -1 to output everything
record_structure = {
    'recids' : {'marc' : '001',
                'weight' : 0,
                'parse-func': parse_controlfield,
                'comp-func' : fields_concat__raw },
    'year'   : {'marc' : '260  c',
                'weight' : 1,
                'parse-func': parse_nonrep,
                'comp-func' : years_comp__raw },
    'title'  : {'marc' : ['245  a', '245  b'],
                'weight' : 2,
                'parse-func': parse_concat,
                'comp-func' : ntfnidf_vectordice_comp__wc },
    'authors': {'marc' : ['100  a', '700  a', '9001 a'],
                'weight' : 1,
                'parse-func': parse_multi,
                'comp-func' : authors_comp__raw },
    'source' : {'marc' : ['773  t', '7112 a'],
                'weight' : 1,
                'parse-func': parse_concat,
                'comp-func' : items_comp__initials }
}
```
Similarity strategies – variations

You may take advantage of a [goup of] field[s] twice using two different methods, for example in record_structure:

[...]

'05authors1' : {'marc' : ['100 a', '700 a', '9001 a'],
            'weight' : 1,
            'parse-func': parse_concat,
            'comp-func' : items_comp__initials },

'05authors2' : {'marc' : ['100 a', '700 a', '9001 a'],
            'weight' : 1,
            'parse-func': parse_multi,
            'comp-func' : authors_comp__raw },

[...]
Similarity strategies – combining results sets

• Depending on the configuration, MarcXimiL will store results in an SQL database (by default).
• In that case, you may combine/merge two or more results sets (for example obtained with two different strategies) using option -m “set1 set2 set3 ...“
• This will perform a geometric mean on the same results pairs.
Practical session & demo

• MarcXimiL version 0.3.6
  – Website :  http://marcximil.sourceforge.net/
  – Download :  http://sourceforge.net/projects/marcximil/files/marcximil-0.3.6.zip/download

• Requirement : Python 2.x (2.5, 2.6, 2.7)
  – Download :  http://www.python.org/download/

• Howto :